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An Expert System Based Sensor Fault Accommodation For Lateral Dynamics Of Aircraft Models

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Abstract

This Sensor faults have been a major area of research for fault tolerant system. Fault accommodation system mainly deals with two specific challenges. First, being an efficient detection of fault and second, a robust model whose estimated sensor signal may be used to reconfigure the system in case of fault. Research shows advancement in model based techniques for fault accommodation. An expert system is presented in this paper with integration oftwo neural network based approaches to provide a robust fault accommodation system. A dedicated knowledge based neural network is used for fault detection only. This detection system is integrated with another model based neural network which provides sensor estimate. Hard sensor stuck fault and intermittent fault for F-8C aircraft and jet transport aircraft is simulated to show the proposed fault accommodation system. The proposed method is tested on closed loop model of the aircraft and validated with ARM target, i.e. SAM3X8E. The ADC and DAC ports of the board were used for interfacing purpose. The input command of pilot and the cockpit display was interfaced with ARM Cortex-M3 CPU.

Keywords: Artificial neural networks, Knowledge based network, fault reconfiguration, Model basedneural network,fault reconfiguration, sensor fault diagnosis

1. INTRODUCTION

Resistive Sensor fault detection (SFD) and reconfiguration is a foremost concern in any reliable flight control system (FCS). Sensors are vital component in aircraft as it is used tomeasure the present state of the aircraft. The output signals from these sensors are required to monitor and control the aircraft flight. It is used to decide the commands required for further aircraft flight in stable region of operation (SRO) in the required flight path. Sensor fault detection (SFD) and reconfiguration is an important issue because the observations from sensors are utilized in the feedback of the control system. Therefore, unrecognized/un-reconfigured sensor faults can lead to risky consequences which may lead to aflight condition, which may be unrecoverable also. It is critical for FCS as a large number of events have been reported [1]. Various conventional methods (hardware and analytical redundancy techniques)have been explored for the sensor fault detection, identification and reconfiguration in dynamic systems [1].References [1]-[4] discusses about various such approaches. The conventional approaches have limitations in various aspects. Model based approach to detect fault based on residuals offers slower fault detection. Faults which are near steady state are also not detected by conventional approaches. Artificial neural network (ANN) has proven to contribute significantly [3]-[10] in the field ofsensor fault diagnosis system. Neural network [NN] or artificial neural network with its interconnected structure comprising of parallel basic processing units is capable of modelling highdegree of nonlinearity.

NNs can be used for design of both model based network or knowledge based network. A knowledge-based system has the knowledge (gained with neural network training) of the system's unstable behavior in case of occurrence of faults. Kim[8] demonstrated the analytical information which was extracted from the sensor measurements and used for sensor fault identification. This was additional to the system’s knowledge. A knowledge-based analytical redundancy with integrated models was proposed by Betta et al [9].Brotherton T et al [10]used advanced military aircraft to validate knowledge base NNs for anomaly detection. Researchers got promising results withknowledge base networks. Sensor fault detection and accommodation (SFDA) using model based neural network(MBNN)was explored by some researchers [3], [4]. A few researchers [8], [10] explored knowledge based NN, independently for SFD in their work. Michail [11] proposed fault detectionscheme which uses an AI approach. Model-based fault detection units can be extended for more than one sensor faults. It requires a bank of estimators. Ref [12] showed hardware implementation of NN based system in FCS.Researchers have explored the versatility of NNs in various dynamical domains.

However, the concept of using integrated approach of different NN models for sensor fault accommodation is not reconnoitered. The work carried out in this areaincludes comparison of NN based SFD with conventional approaches of residual based SFD and is reported in reference [5]. Integration of two approaches of NN, namely Knowledge based and Model based approach for SFDA is proposed for a FCS. Faults are simulated for an aircraft model (F8-C and 747 Jet transport aircraft). Lateral dynamics is used in both case. Fault detection is more crucial in comparison to fault reconfiguration. Fault detection using knowledge based neural networks in this paper is the key contributor in forming robust faultaccommodation system. Model free approach for fault detection, which is capable of covering wider range of faults with KBNNFD, ascompared with previous work has been used. Usage of model based approach, only for reconfiguration is acceptable, once the fault has beendetected effectively and efficiently by KBNNFD. Model imperfections tend to degrade the fault detection performance more than the faultreconfiguration. Ref [5] deals with SFD based on KBNNFD and showed its better performance with respect to many key parameters when compared to conventional algorithmic method. Ref [5] deals with the design of MBNN which provides estimate for Nz sensor. This paper is an extension to ref [5] where NN based methodswas developed for SFD and reconfiguration in F-8C aircraft’s longitudinal dynamics which was a SIMO model.This paper focuses on implementation of KBNNFD and MBNN methods for MIMO model of lateral dynamics of aircraft. Simulation models are used here, however, the actual implementation uses real FCS data. SFD is done using KBNNFD and the output of this model acts as control signal (indicating fault) for reconfiguration.

In case of fault, reconfiguration is provided by the signal estimate of the corresponding MBNN model. This integratedtechnique produces a robust system for sensor faults in FCS. KBNNFD is not taking the input from mathematical model as shown in Fig. 1a, which is normally done in conventional approaches of SFD. MBNN’s estimate is utilized only in case of fault for reconfiguration. Section 2 provides an overview of the literature on sensor fault accommodation methods; in Section 3, the simulation set up is discussed for the detection and reconfiguration of sensor fault in lateraldynamics model of aircraft. Section 4 discusses various training approached of the neural network. Section 5 discusses knowledge based neural network for SFD and reconfiguration of the sensor faultusing model based method of neural networks. The experimental results are presented in section 6. Lateral dynamics of F8C aircraft and 747jet aircraft is used for the same. Hardware implementation result is also presented. Section 7 presents discussion of result and section 8 isabout the conclusion and future scope.

2. Sensor Fault Accommodation Methods

The detection, identification and accommodation of sensor faults in dynamic systems are explored with an extensive variety of conventional approaches [1].Hardware redundancy technique is a traditional method which deals with multiple sensors.Multiple parameters are available for comparison in such case and appropriate one is selected based on various scheme. This hardware redundancy system isbeing used primarily in aircraft like the F-lll, the YF-12, the L-1011 and the F-16 (fighter aircraft). However, this multiple sensor system results in high power consumption,cost and weight/volume[1]. A validated mathematical model is used in analytical redundancy technique. This analytically estimated signal is compared with physical sensor signals of aircraft [2]. The variance between these two signals is known as residuals. The generated residual signal can be utilized for SFD. If this residual signal is beyond a specified threshold, then the fault is declared. It involves processes likestatistical decision theory, state estimation and adaptive filtering. The methods like Luenberger Observers and Kalman filters are very prevalent for estimating the signals [3]. The estimated signal provides reconfiguration of failed sensor. Therefore, it avoids the aircraft to crash or fly beyond the SRO (safe region of operation). Sensor fault accommodation system using such mathematical model is shown in Figure 1a. The figure shows how a mathematical model’s estimate is used for fault detection as well as reconfiguration. Fault indicator signal (using residual methods like Canberra metric etc.) is used as the control signal. This controls the switch for replacement to model’s estimate instead of physical sensor, in case of fault. Such system is called as model based sensor fault accommodation system and accuracy of such system heavily relies on the model (with working assumptions like linearization etc.).NNs are processing method that are inspired by the nervous systems and brain. A variety of NN approaches are explored by researchers for various anomaly detection including Sensor Fault Detection and Accommodation (SFDA). NN has capability to work efficiently in non-linear scenario. Napolitano [3] used NN based methods for SFD in aircraft control system and also showed its advantages over conventional method. Napolitano [4] used nonlinear model of aircraft to show the capability of NN and the results were promising. However, model based NNs were used. Mathematical model based NNs showed better results than conventional algorithmic techniques [2], [3]. Jude V Shavlik [18] presented a survey on knowledge base NN related work. Shalvik highlighted the methods of refining ordinary NNs by using Knowledge base NNs. Brotherton T et al [10] developed a NN based anomaly detector for Advanced military aircraft using knowledge base NNs. Discrimination power to recognize faultsbased on these feature inputs is used. Knowledge based neural network fault detection (KBNNFD) system for FCS of this work uses features likecontrol signal, sensor signals, and pilot’s command. Variations of the signal pattern are used as database for healthy as well as faulty situation is used to train the NNs. This specialized knowledgebased training of NNs makes it more efficient to detect fault. Adding specific knowledge toNNs makes an expert system thatis capable of working efficiently for the given problem. It is just like a skilled operator of specific equipment/complex machine/system. However, it is tough to examine an extensive data set for fault sensitive signals and its values/trend for various cases of fault.

Rules based system is also inadequate keeping number/coverage of rules as the limiting feature. NN training with extensive data makes it capable to learn to work for new unseen data also. Thus, knowledge base NNs are capable of getting adequate knowledge of specific system’s behavior.

This paper explores the integration knowledge base NNs and model base NNs for sensor fault detection and reconfiguration problem, respectively. Knowledge base NN for SFD is a model free approach. Anothermodel based approach of NN is developed only forreconfiguration purpose. These two NN models (trained with different algorithms)are integrated appropriately for the proposedtechnique of NNSFA.

Feature extraction is a crucial step indeveloping aneffective diagnostic system. Offline signal processing with enough experimentation is done forkey signatures identification for SFD. This follows creation of elaborate database which is a superset of various operating conditions. The final extracted features should be uncorrelated with other features. The possibilities of false alarm also need to be explored. NN is trained for SFD for lateral dynamics of two different aircraft model and control system. Faultdetection system independent from modelling error.KBNNFD is found to be superior in various aspects like speed and range of operation. Reconfiguration is done by providing analyticalredundancy which uses MBNN. Function approximation method is used for the given system.Simulationmodel data was used to train NNs.Reference [17] discussed about the robustness and efficiency of NN models. The NNSFA is capable to accommodate the sensor faults in bothdynamics of aircraft. Lateral dynamics of fighter and transport aircraft is used for demonstration of the proposed technique.

3. Simulation Set-up

Aircraft lateral dynamics is used for the study of KBNNFD and MBNN based fault accommodation system. The simulation set-up shows the connection of sub systems, which is simulated in MATLAB Simulink.

Fault induction block shows induction of stuck fault, ‘S’ using N sample switch, which induces fault at 5 sec, i.e. 250th sample with sampling time of 0.02s. The rudder input isgrounded and the aircraft is simulated for roll maneuver only with aileron input of unit step for 5 seconds. Similarly, various instants of faultswere simulated to experiment with the proposed method of NNSFA.

4. Training Approaches of Neural Networks

There are mainly two types of training - Supervised and unsupervised. Supervised learning is used in this work which requires the appropriate training data to supervise the learning of the neural system. The training data and algorithm of NN is decided mainly by the type of application. NNs are used for applications like classification, recognition, detection etc. It depends on the neural architecture, training algorithm and training data.This section focuses on two approaches which primarily depends on type of training data for different tasks. Both approaches are integrated for the proposed SFDA technique.

Knowledge based approach :

NNs are known as data driven methods [13]. Thus data plays a vital role in NNs performance. Knowledge based approach of NN uses data which depicts peculiar behavior of the system involved. Key signature signals are required for the fault detection purpose, which may be intermediate signals of the FCS and can be used for the knowledge of the system. It will have significant fault signatures which will indicate system behavior in presence of faults. This knowledge can be used as training data for NN based on the complexity of the system. A suitable supervised training algorithm will be used to imbibe the knowledge of data into the NN. Thus, this network becomes good enough to differentiate the event of failure (any abnormality) with normal operation.

Model based approach:

Model based methodapproximates the behavior of any system by estimating the relationship between its input signals and output values. The relationship between the input signals and output values may be non-linear also [4]. Such systems have been explored extensively by the researchers [3], [20]. This is because, it is less complex mathematically and still gives a very effective performance [3]. NN based model does a decent task of estimation with the help of various supervised training algorithms. Development of such models requires certain parameters to be defined like NN structure and size. The estimated function's smoothness is decided by 'spread' value. More the smoothness more will be the size of NN so it need to be decided judiciously.More details on design will be discussed in section V.

5. NEURAL NETWORK BASED SENSOR FAULT DETECTION AND RECONFIGURATION

KBNNFD - Knowledge based neural network fault detection:
Knowledge based approach of NN uses data which depicts peculiar behavior of the system involved. Key signature signals are required for the fault detection purpose, which may be intermediate signals of the FCS and can be used for the knowledge of the system. It will have significant fault signatures which will indicate system behavior in presence of faults. This knowledge can be used as training data for NN based on the complexity of the system. A suitable supervised training algorithm will be used to imbibe the knowledge of data into the NN. Thus, this network becomes good enough to differentiate the event of failure (any abnormality) with normal operation.
Feature extraction for KBNNFD method involves a detailed analysis and signal processing which is used to recognize fault signatures. It differs for different aircraft models and respective control systems. The extensive analysis is done for the components involved, its relation with each other and its behavior at different operating condition. Then the significant features can be shortlisted which need to be extracted for implementation of robust decision making module. The database is made which holds enormous knowledge of the system, which in turn is used for training of the NN model. It should be reliable for the diagnosis of variety of untrained/unseen faults also. This heavily depends on the analysis done on signature features extraction which is crucial and special for the fault detection [5]. As NN is trained with the created database, this database should be comprehensive with variety of failure cases. Four features were finalized to proceed with the estimation task of fault detection. This model was capable of differentiating between a healthy system and faulty system (Fig. 3).

KBNNFD Design:
A NN structure of 5-12-1 of feed forward type is fixed. Appropriate number of neurons is fixed in hidden layer with enough experimentation for appropriate generalization. Experimenting with hidden layers neurons, twelve neurons in hidden layer was found to give best performance. Output layer of NN with one neuron will indicate fault. Initially, the NN structure weights and bias values will have small default values. This untrainedNN is incapable to perform any task as it does not have any knowledge in it. Once it is trained efficiently with the appropriate data and algorithm, it will attain the knowledge of FCS involved. After the training, testing and validation of the NN, it becomes capable to perform the fault detection task. Gradient descent backpropagation training algorithm is used for KBNNFD [5]. The final trained NN weights and biases would be updated as per the knowledge given through training and then it will remainunchanged, until further training. The trained NN, KBNNFD block can be interfaced with the FCS.

MBNN – Model based neural network:
Function approximation uses generalized regression neural network (GRNN). The hidden layer follows radial basis function. Output layer is a special linear layer. It follows the algorithm of radial basis function. Observers, Kalman Filters [3] are a few of the popular conventional techniques which is used to provide signal estimate for redundancy purpose in

FCS. Neural networks can also be used to estimate the output signals and relations of various parameters of any system. When a NN is used to model a system, it is called as model based neural network [3],[4]. MBNN estimates sensor signal value which is used to reconfigure the faulty sensor, once fault is indicated by KBNNFD model. The detection of fault and switching control is managed by different subsystem.

MBNN Design:
MBNN function is to model the system behavior and estimate the specific sensor signal of interest. It uses the sampled set of system's input-output pair [5] as dataset to get trained for the relationship between them. The FCS simulation model of Fig 2 is used to create training data vectors. Input-output pair of signals is used by conventional methods also, like full order observers etc. One of the sensors is assumed to be healthy in conventional approaches [2, 3]. For this case, the healthy sensor is β sensor. With experiments, it was found that sampling interval of 0.1 sec is sufficient for signal estimation. Spread value for GRNN function is fixed at '2'. NN structure's size depends on sampling interval and spread value and therefore it should be fixed appropriately. MBNN model was developed and it could estimate ϕ sensor signal successfully. MBNN estimate is utilized in case of sensor failure by replacing the faulty sensor signal, in case of fault, in feedback loop. Fig. 6 and 7 shows plot of MBNN's estimate ('ϕN') and reconfigured 'ϕ' sensor signal. This keeps the aircraft safe and prevents from going beyond SRO.

6. Experimental Results:
The complete simulation set-up is shown in Fig.2. The methods involved in developing simulation models of FCS are provided in reference [7]. Aileron input of FCS is actuated using a step command of '1' radian for 5 seconds from 2s to 7s as shown in Fig. 4 to 8. 'ϕ' sensor failure is simulated in Fig 5,6 and 7.The subsystem named 'Fault Induction' simulates stuck sensor fault. Sensor 'ϕ', which is denoted by 'ϕS' is induced with the stuck fault. 'Controller' subsystem provides control law (Kx) in the feedback loop. The x vector comprises of the failed sensor state also and therefore in the scenario of fault, xFaulty state vector replaces x state vector and thus fault propagates with control law (K*xFaulty) signal in loop. This generates closed loop instability in other elements of 'x'state vector as shown in Fig. 4. 'KBNNFD' subsystem detects the sensor fault and generates control signal which uses 'MBNN' subsystem estimate ('ϕN') to reconfigure the failed sensor signal. The threshold value for KBNNFD output control signal is fixed at '0.8' to avoid false alarm. RECONFIG subsystem provides reconfiguration for failed ϕ sensor. The estimated signal ('ϕN') from 'MBNN' subsystem is switched instead of faulty sensor signal ('ϕ') in the feedback loop, in case of fault (Refer Fig. 2). Controller also does the task of incorporating reconfigured 'ϕ' state in the feedback loop from RECONFIG subsystem. In situation of 'no fault', the 'RECONFIG' subsystem continues to keep 'ϕ' in feedback loopthrough 'controller' subsystem.

Experimental Investigations of F8C Aircraft:
The stable sensor output (β & ϕ) is shown in Fig. 3 for healthy scenario. The aileron input actuator command is also shown in Fig 3. This figure is used to show the extracted features which is used for training of KBNNFD. The plot shows the range of operation of all signals for a specific actuator command. In case of absence of fault accommodation, aircraft flight may cross its SRO limitsas shown in Fig. 4. Figure 5 to 7 are used to show threeevents of stuck sensor fault that wereexaminedandisbriefed in Table I.

Experimental Investigations of 747 Jet Aircraft:
Boeing 747 jet aircraft [7] was also used for the demonstration and validation of the proposed technique. The model at flight condition of Mach 0.8 and height 40,000 ft. is used. Lateral dynamicsis used and sideslip angle sensor fault accommodation was implemented and the result for one case is shown in Figure 8.

Hardware Implementation:

The Simulink model is executed in external mode on ARDUINO. The aileron input command, i.e. a step signal is actuated with help of a switch (push button) which is kept ‘ON’for 5 seconds. External input is used here via an ADC pin. Bilinear transformation was used to discretize the simulation model. The sampling frequency was fixed at 50Hz. Delay blocks were required in case of algebraic loop error in the process of conversion.Fault indicator output is seen oninterfaced DSO (Digital storage oscilloscope). The output layer’s neuron output which indicated fault is provided to the uniform encoder block. Theuniform encoder block is responsible for conversion of discrete signals into bit rates. DAC of ARDUINO DUE was used to see the output control signal which was fault indicator. It was connected through uniform encoder block output. KBNNFD’s output neuron indicator is checked on a DSO using an output pin of the DUE. The coder used isert.tlc which is embedded real time coder format. The output can be observed on Simulink scope with the model run on targethardware by using the external option. Otherwise, the model can be made standalone also and the output can be checked on external interfaced DSO with the ARDUINO. The same is shown in Fig 9. A small delay can be seen because of hardware timing constraints. The change in signal was almost instantaneous in the simulation model.

7. Discussion of Results

NNSFA system is developed for ϕ sensor failure in F-8C aircraft model and β sensor of jet transport model. Both were lateral dynamics model. Stuck faultsin the range of ‘0’ to ‘0.72’ radian at any time instant can be accommodated by NNSFA. Fifth plot of Fig. 5indicates that with appropriate action, both aircraft sensor outputs remain in SRO.As KBNNFD method does not depend on any mathematical model to detect fault, there is no possibility for error due to imperfections in model. Imperfect models can be assumed equivalent to non- linearities. The model parameters (A, B, C, D matrices elements) are randomly altered by ±10% from their nominal values using normal distribution to model this. KBNNFD was found to be valid for this case also. MBNN successfully estimates ϕ sensor value of F-8C aircraft. This two-way integrated method of NNSFA using the KBNNFD and the MBNN proved to better in the following ways:

- Independent of mathematical model estimate for SFD (Model free approach).
- Faults near steady state was also accommodated (Fig. 6) which is not the case with residual method [3].
- Faster accommodation of faults: up to 5 sec faster than conventional method for various fault cases [8].
- Accommodation of sensor faults in the transient state and intermittent duration (Fig. 7).
- Handled aircraft model non-linearities up to ±10%.
- Sensor noise up to ±8% was manageable.

The hardware implementation validated the proposed method for accommodation of fault. The closed loop timing constraints were successfully satisfied for different cases of fault, one of which is shown in Figure 9.

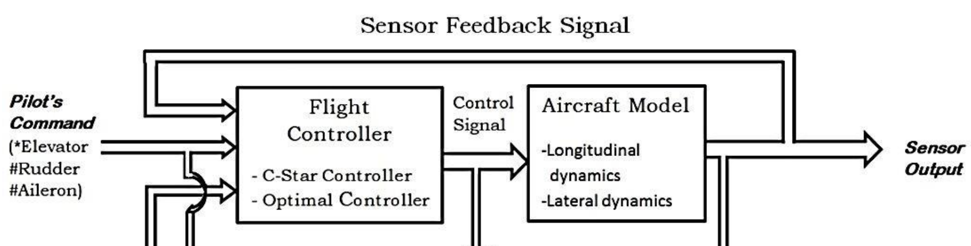


Figure 1a. SFDR using analytical model

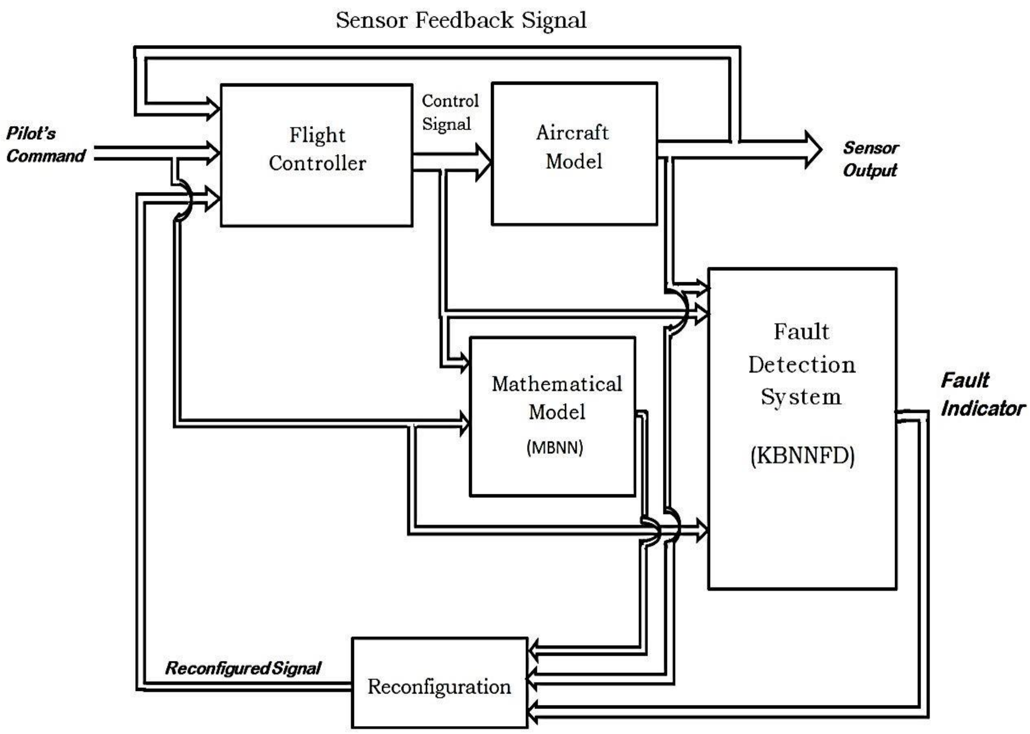


Figure 1b. NNSFA for FCS

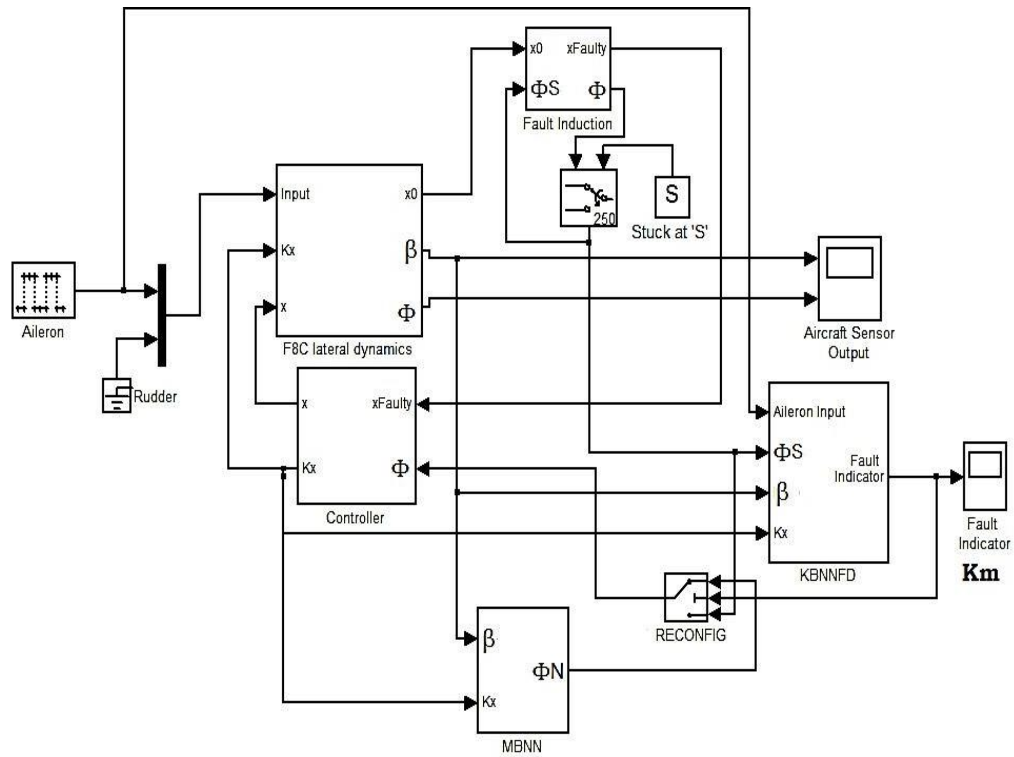
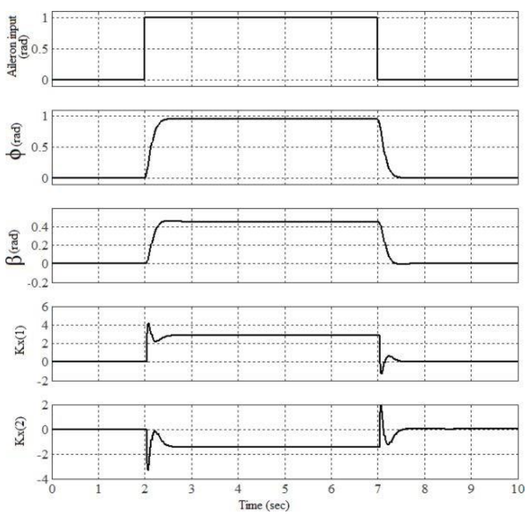


Figure 2. F8-C Lateral dynamic's Simulink model of NNSFA



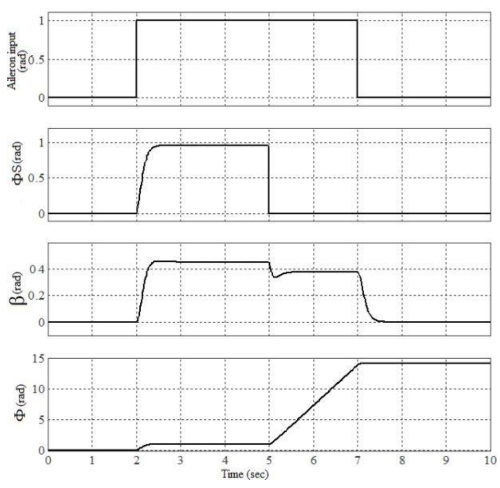
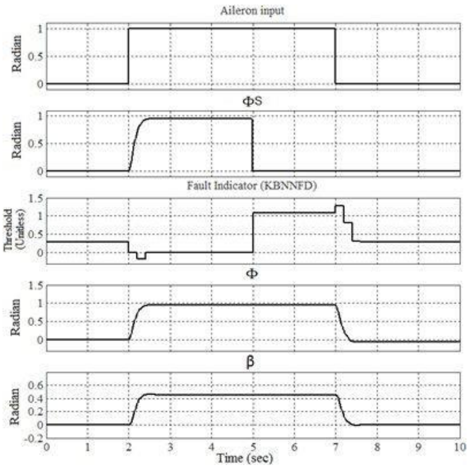


Figure3. KBNNFD extracted features (Healthy scenario)

Figure4. FCS states with sensor fault (without reconfiguration)



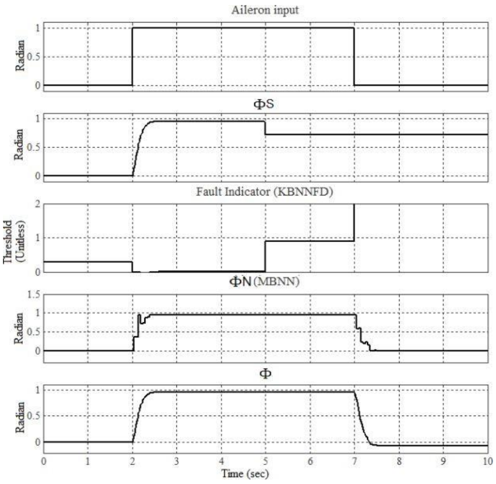
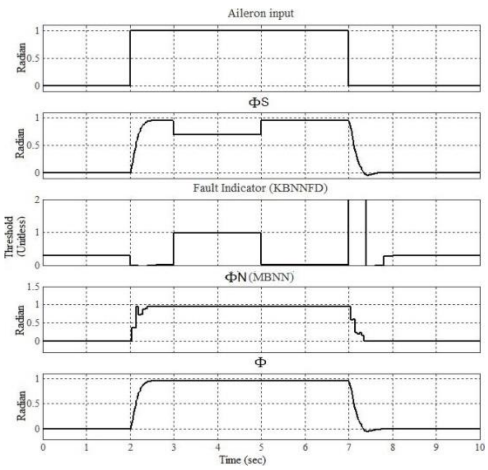


Figure5. ϕ sensor stuck fault at 5s at '0' value



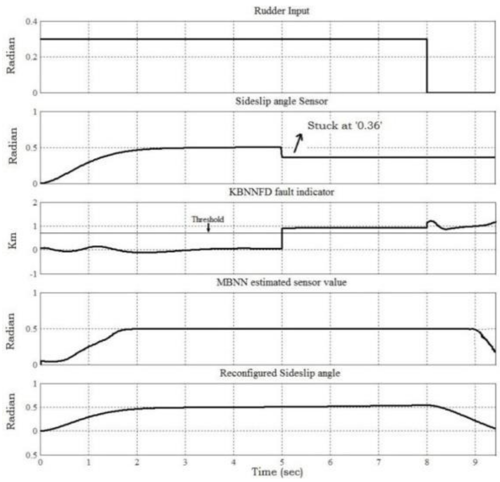


Figure7.ϕ sesnsor intermittent stuck fault from 3 to 5s at '0.7' value

Figure8. Sideslip angle sensor fault at 5s at 0.36 value (for 747 Jet transport aircraft model)

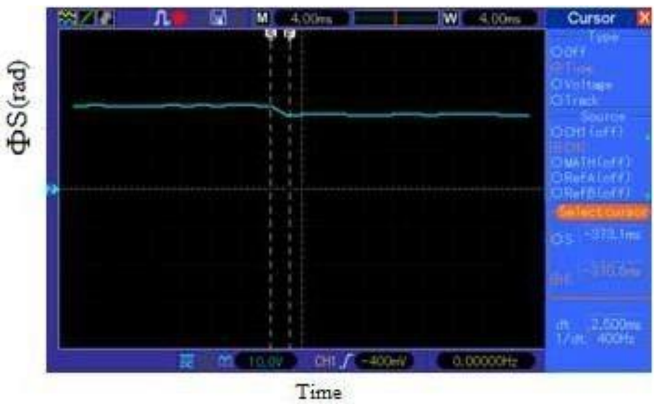


Figure 9. Small delay seen in reconfiguration with hardware implementation

Table I: Fault cases experimented for investigations of NNSFA for lateral dynamics of F8-C aircraft model

S.No.	Φ sensor's stuck value (rad)	Fault Induction time (sec)	Figure
1	0 (Stuck at '0')	5	Fig. 5
2	0.72(Steady state)	5	Fig. 6
3	0.7	3 to 5 sec (Intermittent fault)	Fig. 7

8. CONCLUSION AND FUTURE WORK

NNSFA technique is proposed for ϕ sensor failure in F-8C aircraft model and 747 jet aircraft (lateral dynamics). The F-8C FCS is used for verification of proposed method of NNSFA.KBNNFD detected sensor fault. This NN model is implemented by training with knowledge base data which consists of selected features of the system involved. KBNNFD model is trained with supervised algorithm of gradient descent back propagation. KBNNFD's fault detection follows a model free approach. It has proven to be better than conventional approach of SFD [8].

Additional NN was developed specially for estimating the selected sensor signal and it is used only for reconfiguration purpose, in cases of fault. This model based NN (MBNN) is developed using radial basis function of GRNN. Unlike the older methods, MBNN issued only for reconfiguration of fault. NN models are trained with the database which is generated from simulation model of lateral dynamics of aircraft and its associated controller for verification of the proposed technique. The proposed technique of NNSFDA with its two-way integrated approach, using KBNNFD (for detection of fault) and MBNN (for reconfiguration of failed sensor), has proven to provide a robust sensor SFDA. Various cases of stuck fault like stuck '0' fault, transient state fault, steady state fault and intermittent stuck faults were tested and verified successfully by NNSFA.NNSFA successfully accommodated fault with an imperfect model of aircraft (±10% variations) and also in presence of sensor noise (±8%). The proposed technique can be implemented for more complex nonlinear systems also. Hardware implementation was done to validate the system. A minimal, acceptable delay is seen in the case of the reconfiguration of the sensor fault. This work can be extended to optimize the size of MBNN by experimenting with other NN algorithms. NNSFA can be explored for drift faults. Other NN algorithms or structures may be explored to achieve best approach for NNSFA. Hardware implementation using FPGA or other hardware can be explored.

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